

## MISSION SCHEDULING

Christine GASPIN

Centre d'Etudes et de Recherches de Toulouse  
 Groupement d'Intelligence Artificielle  
 2 avenue Edouard Belin 31 055 Toulouse Cedex  
 Tel: 61 55 71 11 poste 7442  
 Telex: 521 596 F onecert

## 1 Introduction

Problems that have combinatorial complexity are generally said NP-complete problems (meaning that there are no polynomial algorithm for finding optimal solutions). About solving combinatorial optimization problems, standard operation research methods are effective for little problems but they often failed when more complex problems involving many variables and constraints are to be solved.

Whenever we cannot use standard methods, more suitable "hybrid" systems merging operation research and artificial intelligence techniques but very domain dependant and less restricting, work with specific heuristics and offer non optimal but very satisfying solutions.

A more general "hybrid" system, OSCAR, based on an automatic intelligent reasoning has been built in [9] for the mission scheduling problem, using a general assignment algorithm designed to work with a variety of heuristics and rules to make choices and define the reasoning strategies.

NP-complete problems also have been shown to be solved by a neural network approach if they can be formulated as optimization problems [3]. Indeed many researchers have shown that neural networks are satisfying constraint systems and

**Abstract**

*We investigate through a mission scheduling problem how a neural network can work compared to a hybrid system based on operation research and artificial intelligence approach. Then we present a discussion to demonstrate the characteristic features of each one.*

**Keywords**

Scheduling, assignment, operation research, heuristics, optimization, neural network, self-organization

that we are able to design neural networks giving very good solutions for operation research problems.

A number of papers have been yielded which compare different neural network techniques for solving optimization problems [5,6,7].

Whenever it is known [3] that computational power and speed of collective analog networks of neurons in rapidly solving optimization problems has been demonstrated, we ask what are really interests of a neural approach compared to other approaches through a specific assignment problem.

When OSCAR works with local measures, we propose to compare, for the same assignment problem, such a system to an optimization method based on neural networks involving a global measure.

After briefly presenting the assignment problem, we give the principle of the general assignment algorithm then the neural network approach. Then we discuss about properties of both approaches giving our topics about weakness and strength of each one.

## **2 The scheduling problem**

### **Interests**

A spacecraft scheduling is a difficult problem because of a large number of different and interacting constraints, uncertainty and often situation-dependant optimization

criteria which make the search process computationally complex.

The mission scheduling problem consists of finding both a set of resources and a temporal position for each elementary lower-level activity. Our interest deals with three points:

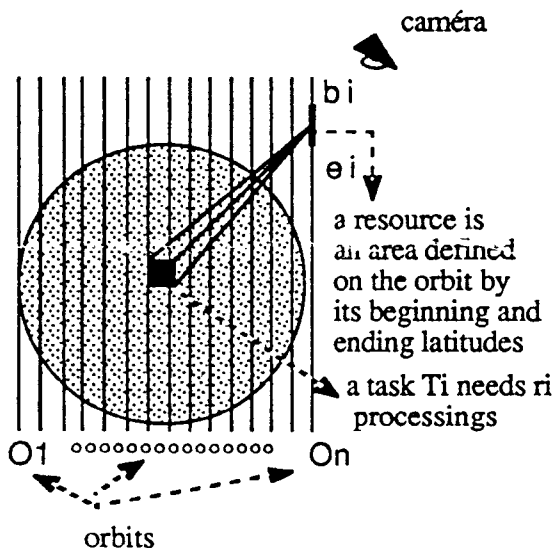
- Temporal relative and absolute constraints
- Activities which are elementary action to be performed on the spacecraft or on the ground requiring one resource-group to be chosen among various possible resource-groups.
- Pointwise unsharable resources defined in [9] as resources involving both the assignment and scheduling problems. Such a resource is for example a camera and the camera assignment problem has to be the following.

### **The camera "resource"**

An heliosynchronous spacecraft payload consists of cameras with tilting capabilities. Therefore, its workload consists of activities  $A_i$  which are processed by taking  $r_i$  pictures of a given area from a possible set of specified orbits. The area is defined on the orbits by its beginning ( $b_i$ ) and ending ( $e_i$ ) latitudes and has a given width. Mirrors allow to take pictures of the landbelt not only just below the satellite but also above several landbelts beside the central band.

Since weather conditions can alter the quality of a picture,  $r_i$  pictures are required to satisfy an activity i.e. get a good picture of all the expected areas.

Let  $r_i$  the required number of processings of activity  $A_i$ . The workload is built dynamically and thus the assignment of the activities must be updated after each request. The sequence of orbits is given and cannot be changed in any way. Therefore at a given time  $t$ , the following orbits  $O_1 \dots O_n$  are described with the activities which are assigned to.



Why this is a "conflict-solving" system is that in this activity assignment problem we have to make choices that is to find a resource (an orbit interval) among several possible unsharable resources respecting constraints.

### 3 A "hybrid" system: OSCAR

OSCAR merges operation research and artificial intelligence methods for solving a large class of spatial missions assignment problems (more precisely scheduling problems).

The set of problems OSCAR is able to solve is the following :

*given a set of activities, the goal is to find both a set of resources and a temporal position for each elementary activity to process.*

Let us define:

#### - An activity

cannot be split and has to be assigned on the same resource-group. Several resource-groups are possible choices for an activity

#### - A resource-group

is defined with

- . a set of physical resources
- . a time window
- . a duration
- . temporal constraints

#### - Physical resources

are to be sharable or unsharable, consummable (memory) or not (electrical power, camera).

#### - Temporal constraints

are **absolute** (beginning and ending times of an activity are bound to stay within a given interval) or **relative** (between two activities).

Therefore the goal is to find for each activity

- . a resource-group
- . an exact temporal position

This approach is **incremental** in that an activity enters one after another one from the set of the all activities in a growing context. The current context is a view of already assigned activities but it is possible to put this assignment into question. The philosophy is the following:

Let A be an activity to be entered in the context

- If the current context has enough room for A, one of the possible resource-groups is assigned to A.

- Otherwise, the minimal sets of activities that prevent A from being assigned one resource-group are defined. Then a minimal set of activities is chosen, ejected from the current context assigning a group-resource to A, and has to be re-planned.

- If one of the ejected activities cannot be re-entered into the context, another minimal set is chosen: there is a failure

- If all the minimal sets fail, it is the total failure

- If all the ejected activities are to be re-planned, the process succeeds

It has been proved that the general assignment algorithm has the following properties :

- It **terminates**.

- It is **complete**: if a solution exists, it finds it.

- Theoretical and practical studies about the average computational **complexity** of the algorithm have shown that except for few very constrained cases, the average number of activities that have to be re-planned doesn't depend on the number of activities but only depends on the saturation rate of the context (rate activities /possible resources).

Specific and general heuristics are used for choosing:

- A group-resource in the context

- A minimal set of activities

OSCAR has been successfully tested on camera resource assignment problem concerning an Earth-Obsevation Satellite.

## 4 The neural network approach

We are interested here in solving a complex optimization problem in parallel without learning process. About solving constraint satisfaction problems [10] gives three neural networks models :

- The Hopfield network [1].
- The Boltzmann machine [4].
- The Tank and Hopfield network [3].

Our goal is not here to compare the three models applied to a specific problem (we find comparisons of models through the travelling salesman and the graph bisection problems in [5,7]) but we want to show how they efficiently can help to solve an assignment problem, what are their weakness and strength compared with the previous approach.

We use both Hopfield networks and Boltzmann machines during our simulations.

These models consist of a large number of computing elements called units that are connected to each other by bidirectional links and this massive interconnection gives them an important computational power.

With each unit  $u_i$  a binary value is associated, denoting its state "0" or "1," (on or off). Therefore, at a given time the network can be represented by a state vector. Weights on links are symmetric, (having the same strength in both directions). A solution is given by a configuration  $C$  of the network that is the state vector. An "objective" function of a global configuration is defined by analogy with statistical mechanics energy

$$E = -1/2 \sum_i \sum_{j \neq i} w_{ij} s_i s_j - \sum_i I_i s_i$$

where

$w_{ij}$  is the strength of connections between units  $u_i$  and  $u_j$ ,

$s_i$  is the state of unit  $i$ ,

$I_i$  is the threshold of unit  $i$ .

If the units change their states one at a time ( $0 \rightarrow 1$ ), given a configuration  $C$ , then firstly a neighbouring configuration  $C'$  is generated, changing unit  $u_i$  state and secondly it is evaluated.

Because the connections are symmetric, the difference between the energy of configuration  $C$  and  $C'$  can be determined locally by the unit  $u_i$  and

$$\Delta E_i = E_{s_i=0} - E_{s_i=1} = \sum_k w_{ki} s_k + I_i$$

thus allowing a parallel execution.

In an Hopfield model the rule decision is :

$$s_i = \begin{cases} 0 & \text{if } \Delta E_i < I_i \\ 1 & \text{otherwise} \end{cases}$$

In the Boltzmann machine, the units are in one of the two states determined as a probabilistic function of the states of its neighboring units (these which are connected to) and the weights on its links to them. The acceptance probability in changing a unit state is

$$p(s_i = 1) = 1 / (1 + \exp(-\Delta E_i/T))$$

where

T is the computational temperature used in simulations as a control parameter associated with a simulated annealing process which is a statistical generalization of hill-climbing optimization methods. It allows to make uphill moves instead of settling in local minimum.

$T=0$  is the limit-case used in the Hopfield model.

The dynamics of evolution of these systems states follow a simple rule (above) and is asynchronous (a unit is randomly chosen and tries to change its state given its inputs).

The updating rule of a unit state is an energy optimizing rule (minimizing / maximizing). Modifications of units states continue until a stable state is reached, that is, an energy optimum is reached.

## Mapping a satisfaction constraints problem

For mapping a satisfaction constraint problem we have to:

- Find a representation of the problem as to be solved by a neural network.

Indeed, the literature often involve schemes which are operation research ones (matrix, graphs) and we have to investigate if it is relevant to relate operation research representation problems to neural techniques.

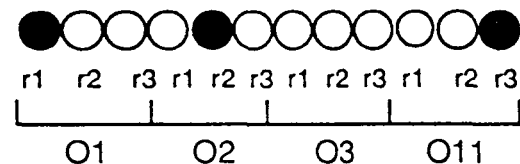
The solution to the assignment problem consists of an optimal assignment with the respect to the interacting constraints.

To map this problem onto the computational network, we require a representation that needs to be decoded. We have chosen a representation scheme in which the final assignment is specified by a configuration of the network.

For example, if an activity  $A_i$  requires  $r_i = 3$  processings and if a possible set of resources for  $A_i$  is

$$Q_i = \{O1(1\ 10)\ O2(3\ 13)\ O3(0\ 9)\ O11(10\ 18)\}$$

a possible solution is given by



- The processing  $r_1$  of  $A_i$  is on the orbit  $O1(1\ 10)$

- The processing  $r_2$  of  $A_i$  is on the orbit  $O2(3\ 13)$

- The processing  $r_3$  of  $A_i$  is on the orbit  $O11(10\ 18)$

- Define units. Therefore a unit is the elementary information to process in this optimization problem and it means :

" a possible choice " for assigning the activity  $A_j$  to the resource  $O_j$  respecting its temporal constraints.

This representation scheme is natural since any activity can be assigned to any one in its related possible set of resources.

The number of units required for a problem where  $p$  activities are involved is therefore

$$N = \sum_p n_p \text{ units}$$

where

$$n_p$$

$$=$$

(the number of processings of activity  $p$ )

\*

(the number of possible orbits intervals which can be assigned to activity  $p$ )

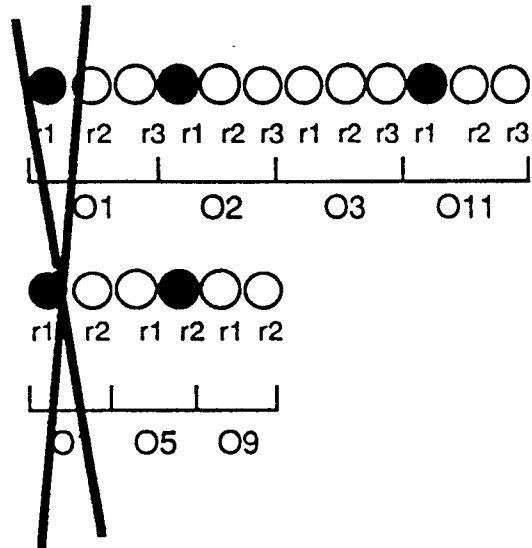
that is the number of units for representing the activity  $A_p$ .

Our point is that resources are unsharable that is

- any part of any orbit cannot be simultaneously shared between two activities. If  $A_{i'}$  is another activity and  $Q_{i'}$  its possible set of resources and  $r_{i'}=2$

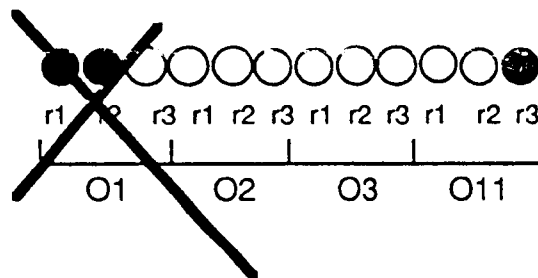
$$Q_{i'} = \{O1(1\ 10)\ O5(5\ 14)\ O9(7\ 16)\}$$

we cannot find the following solution scheme

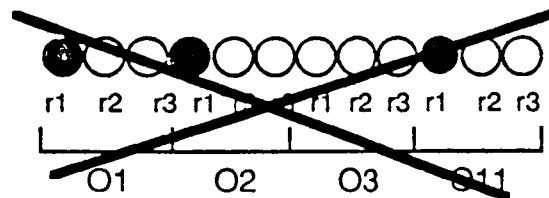


that is we cannot find  $r1$  on orbit  $O1$  for activity  $A_i$  and  $r2$  on orbit  $O1$  for activity  $A_{i'}$ .

- different processings of the same activity cannot share the same part of an orbit. So we cannot find the following solution scheme

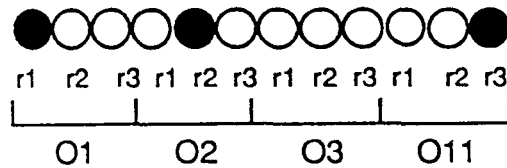


- the same processing cannot be assigned more than one resource at a time. So we cannot find



that is  $r_1$  cannot be assigned to orbits  $O_1$  and  $O_2$

- an activity try to assign all the processing it requires:



The "objective" is to occupy as better as possible the all set of resources.

Because of these choices a unit  $u_{ijk}$  means the possibility for activity  $i$  to assign processing  $j$  on orbit  $k$

- **Define the connections** that is define what a link is with the respect to the constraints and the "objective" of the problem.

Weights on links represent a weak pairwise constraint between two hypotheses.

$i$  : index giving the orbits  
 $j$  : index giving the realizations  
 $t$  : index giving the tasks

Connections are built between links satisfying the following constraints

### Inhibitory links

.Two processing of the same task do not share a part of the same orbit.

.Two processing of different tasks do not share a part of any orbit.

. A task  $T_i$  can't plan more than  $r_i$  processing

### Excitatory links

. Each unit activates a processing of another orbit

- **Define what are the right connection weights**

For computing a solution to the problem, the network has to be described by an energy function in which the most stable state of the network is the best assignment. Our energy function is the following

$$E = -a \sum_{i,i' \in c1} (r_i^* (p_i + p_{i'})) s_i s_{i'} \\ -b \sum_{i,i' \in c2} (\max(p_i, p_{i'})) s_i s_{i'} \\ -c \sum_{i,i' \in c3} (\min(p_i, p_{i'})) s_i s_{i'} \\ +d \sum_{i,i' \in c4} (r_i^* (p_i + p_{i'})) s_i s_{i'}$$

where

$$c1 = \{u_i, u_{i'} / \text{activity}_i = \text{activity}_{i'} \\ \text{orbit}_i = \text{orbit}_{i'} \\ \text{processing}_i \neq \text{processing}_{i'}\}$$

$$c2 = \{u_i, u_{i'} / \text{activity}_i = \text{activity}_{i'} \\ \text{orbit}_i \neq \text{orbit}_{i'} \\ \text{processing}_i = \text{processing}_{i'}\}$$



$$c3 = \{u_j, u_j' / \text{activity}_j \neq \text{activity}_j', \\ \text{orbit}_j = \text{orbit}_j', \\ (\text{processing}_j \neq \text{processing}_j') \\ \text{or} \\ (\text{processing}_j = \text{processing}_j')\}$$

$$c4 = \{u_j, u_j' / \text{activity}_j = \text{activity}_j', \\ \text{orbit}_j = \text{orbit}_j', \\ \text{processing}_j = ((\text{processing}_j' + 1) \\ \text{mod } (\text{number of processing}_j))\}$$

$a, b, c, d > 0$  are parameters

$p_j = F(\text{number of possible resources for } A_j, \text{ number of activities for which orbit related to } u_j \text{ is a possible resource, number of processings needed by } A_j)$

This function gives advantage to the less requested resources.

## 5 Starting a discussion

### - Complexity

Complexity is defined in computer science by :

- Spatial complexity
- Temporal complexity

The neural network simulations always converged giving satisfying solutions from an engineering point of view for little examples with 256 units (25 activities and 21 resources) or less.

If the complexity has been theoretically and practically studied

in the R.O. and I.A. approach giving very interesting results about the average computational complexity of the algorithm, for very constrained cases, combinatorial problems are again involved.

Theoretical studies are being made for the neural net one. Nevertheless, in this application the neural network appears to converge with the number of units.

If many activities are involved in a problem, a great number of possibilities appears. Therefore, solving such a complex optimization problem needs a large number of units and a highly connected network. But because of the  $10^{11}$  neurons and  $10^6$  connections from each one in the nervous system and very encouraging results which appear in the domain, it is relevant to investigate how the computational power of these networks can help to solve optimization problems.

Moreover, neural networks are parallel systems which are functionally implementable .

### - Locality of taking decisions

The assignment algorithm decides with locality. Indeed, when a new task enters, only its possibility of assignment is investigated.

The new task is or is not able to be planned. No global criteria is taken into account. An already planned task is ejected only if it is sure to get another assignment.

A neural net approach also decides locally about an assignment. Indeed the model is based on computational locality of decision in the units. Moreover, it takes immediately into account the constraints on other units that is the constraints of the problem. Therefore, there is a "microscopic" decision system (cooperation /competition) in every unit because of the neighbourhood.(defined by the connections.)

### Example

Activities	1	2	3	4
number of processings	2	2	2	2
latitude of begin	1	1	1	1
latitude of end	6	6	6	6
list of orbits	o1	o3	o3	o4
	o2	o4	o6	o5
	o3		o1	

### - Global / incremental decisions

The set of constraints mapped on the connections to a unit makes the unit to take locally a global decision that is it computes a global criteria to optimize.

We give for example in [8] a criteria to maximize "the probability of satisfying all the activities". Therefore an already planned task is ejected if the new activity optimizes the "objective" function satisfying the constraints given by the neighbours (the units which it is directly connected to).

In comparison, the research operation and artificial intelligence approach is an incremental decision process in which no global criteria is computed.

If the objective is to use all the ressources realizing the best assignment we find the following results for each approach:

In this example the R.O. and I.A. approach can only cope with two activities:

-T1 enters and is satisfied with T1 on orbits O1 and O2  
or  
T1 on orbits O1 and O3  
or  
T1 on orbits O2 and O3.

-T2 enters and is satisfied with T2 on orbits O3 and O4, and T1 on orbits O1 and O2.

-T3 cannot be satisfied without definitively ejecting T1 or T2

-T4 cannot be satisfied without ejecting T2

In that case, our network satisfied T1, T3 and T4, i.e. three tasks:

-T1 on orbits O1 and O2  
or  
T1 on orbits O1 and O3  
or  
T1 on orbits O2 and O3

-T3 on orbits O1 and O6  
and T1 on orbits O2 and O3  
or  
T3 on orbits O3 and O6  
and T1 on orbits O1 and O2.

-T4 on orbits O4 and O5  
and T3 on orbits O1 and O6  
and T1 on orbits O2 and O3  
or  
T4 on orbits O4 and O5  
and T3 on orbits O3 and O6  
and T1 on orbits O2 and O3.

## - Programming complexity

In the neural network formulation of an optimization problem, the constraints and the criteria to optimize are expressed inside the objective function. Thus by optimizing the objective function we optimize the satisfaction of the constraints. Moreover, this approach provides an efficient and very simple technique for mapping the constraints on the links between units.

In the R.O. and I.A. approach, constraints on resources and activities are these which tend to reduce the combinatoric aspect and that is why the constraint-base reasoning is a more complex propagation mechanism.

## 6 Conclusion

We have described here how an optimization problem can be rapidly and easily mapped on a neural

network and provide encouraging results in comparison with an operation research and intelligence artificial approach.

Nevertheless for neural networks which deal with such complex combinatorial optimization problems, the difficult task consists of finding weights of the connections. Indeed, because the solutions to these problems are not known as in other problems involving learning algorithms [6], they must be established by the designer.

Our interest is now to design a mapping method for solving constraint satisfaction problems (more precisely scheduling problems) through applications exploration and theoretical results.

## 7 References

- [1] HOPFIELD, J.J.,  
*Neural Networks and Physical Systems with Emergent Collective Computational Abilities*, Proc. Nat. Academy Sciences, USA, 79 (1982)2554
- [2] S. KIKPATRICK, C. D. GELATT Jr., M.P. VECCHI,  
*Optimization by Simulated Annealing*, Science(220),1983, p.671
- [3] HOPFIELD, J.J. and D.W. TANK,  
*Neural Computation of Decision in Optimization Problems*, Biological Cybernetics, 52(1985) 141

- [4] J. McCLELAND, D.E. RUMELHART and al., *Parallel Distributed Processing*, vol. 1 and 2  
The MIT PRESS (1986)
- [5] J.R. ANDERSON and C.PETERSON *Neural Networks and NP-Complete Optimization Problems. A performance Study on the Graph Bisection Problem*, MCC Technical report Number: EI-287-87, December 14, 1987
- [6] Emile H.L. Aarts, Jan H.M. KORST, *Boltzmann Machines and their Applications*, Proc. of Parallel Architectures and Language, Europe Conf., June 1987, Eindhoven, The Netherlands
- [7] James H. CERVANTES and Richard R. HILDEBRANT *Comparison of Three Neuron-Based Computation Schemes* Proc. of IEEE First Intern. Conf. on Neural Networks, Vol.III p. 657, San Diego, California, June 21-24, 1987
- [8] Ch. GASPIN, P. BOURRET and M. SAMUELIDES, *Neural networks for optimal planning of a camera on board a satellite*, Proc. of Neuro-Nîmes, Nov.16-17 , 1988
- [9] C. BADIE, G. VERFAILLIE *OSCAR : A hybrid system for mission scheduling*, *A.I. Applications for Space Projects*, European Space Agency ESTEC Noordwijk The Netherlands, November 15-16-17 1988
- [10] Mark DERTHICK and Joe TEBELSKIS *"Ensemble" Boltzmann Units have Collective Computational Properties like those of Hopfield and Tank Neurons*, Neural Information Proc. Systems, Dana Z. Anderson Editor, American Institute of Physics, New York